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Research Article

SCALABLE SUSPICIOUS ACTIVITY DETECTION USING TERADATA PARALLEL ANALYTICS AND TABLEAU VISUAL EXPLORATION

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ABSTRACT

The rapid growth of enterprise data has made traditional rule-based methods insufficient for identifying complex suspicious activities across large and heterogeneous datasets. This research presents a scalable suspicious activity detection framework that leverages Teradata's parallel analytical engine for high-performance data processing and Tableau's interactive visual exploration for intuitive pattern interpretation. The system integrates distributed feature extraction, anomaly detection models, and visual dashboards to support real-time investigation and decision-making. Experimental evaluation shows significant improvements in processing speed, anomaly detection accuracy, and analyst efficiency compared to conventional approaches. The results demonstrate that combining Teradata's scalability with Tableau's visual intelligence creates an effective solution for modern enterprise surveillance requirements.

Keywords: Suspicious activity detection, Teradata, parallel analytics, Tableau visualization, anomaly detection, enterprise data warehousing, visual analytics.

I. INTRODUCTION

The exponential growth of transactional and operational data across modern enterprises has increased the difficulty of detecting suspicious activities using traditional rule-based systems. These static approaches often fail to capture evolving behavioral patterns, hidden correlations, and subtle anomalies within high-volume datasets [1]. As organizations expand their digital footprints, the need for scalable analytics frameworks capable of processing massive data streams in real time has become crucial for maintaining operational security and regulatory compliance [2], [3]. Teradata's parallel processing capabilities provide a foundation for handling such workloads efficiently, while advanced visualization platforms like Tableau enable analysts to interpret complex analytical outputs intuitively [4].

Recent studies emphasize that anomaly detection systems are most effective when they combine statistical modeling, machine learning, and visual analysis to uncover irregular patterns that are not easily identifiable through manual inspection [5], [6]. Parallel data-processing architectures have shown significant promise in scaling anomaly detection algorithms to enterprise-level datasets by distributing both computation and storage across clusters [7]. At the same time, visual exploration tools facilitate rapid pattern recognition, assisting human analysts in understanding outliers and contextualizing anomalous behaviors [8], [9]. However, few integrated frameworks have successfully united high-performance analytical engines with interactive visualization platforms in a cohesive suspicious activity detection pipeline.

This paper contributes to filling this gap by introducing a scalable suspicious activity detection framework that leverages Teradata parallel analytics for large-scale anomaly processing and Tableau visual exploration for enhanced interpretability. The proposed system incorporates distributed feature extraction, anomaly detection algorithms, and real-time visualization dashboards, enabling analysts to evaluate suspicious events with improved precision and reduced cognitive load. By integrating automated analytical intelligence with interactive human-driven insight, the framework enhances both detection accuracy and investigative workflows [10], [11].

The main contributions of this work are threefold. First, we design a unified analytical architecture that integrates Teradata's parallel computation with Tableau-based visual intelligence for enterprise-scale anomaly detection. Second, we evaluate the performance and scalability of the system across several real-world operational datasets using statistical and machine-learning techniques [12], [13]. Third, we demonstrate how visual exploration combined with automated anomaly scoring improves decision-making efficiency for security and compliance analysts. These contributions collectively highlight the importance of combining computation, visualization, and domain expertise in enterprise surveillance environments.

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The rest of this paper is organized as follows. Section II presents a review of related research in anomaly detection, scalable analytics, and visual intelligence systems. Section III describes the proposed methodology, including data preparation, Teradata analytical workflows, and Tableau integration. Section IV outlines the experimental setup, datasets, models, and evaluation metrics. Section V discusses the results, including performance improvements and visualization insights. Finally, Section VI concludes the paper and outlines future research possibilities.

II. BACKGROUND & RELATED WORK

Detecting suspicious activity at enterprise scale has long relied on statistical modeling and rule-based systems, which often struggle to capture evolving behavioral patterns across large, heterogeneous datasets. Early work by Bolton and Hand (2002) and Chandola et al. (2009) demonstrated the limitations of traditional anomaly-detection approaches that fail to scale with increasing transaction volumes and complexity [16], [17]. These foundational studies revealed that anomalous behaviors in financial or operational datasets are often subtle, multi-dimensional, and masked by noise—making them difficult to detect without more advanced computational techniques.

Later research shifted toward multi-resolution and time–frequency analysis, where wavelet and STFT methods were applied to model irregular temporal dynamics in financial systems. Mallat (1989) and Daubechies (1992) developed the mathematical foundations for wavelet decomposition, which were later adapted by Lee and Park (2011) to financial anomaly detection [18]–[20]. These works showed that time–frequency features can reveal short-lived spikes, hidden periodicities, and spectral distortions that rule-based systems rarely detect. However, they lacked a scalable architecture capable of applying such computations at enterprise-scale workloads.

Parallel and distributed analytics frameworks have made significant progress in addressing scalability limitations. Studies by Zhao et al. (2016) and Singh and Kaur (2014) demonstrated that distributed engines such as Apache Spark can process millions of records efficiently while supporting computationally intensive transformations [21], [22]. These systems enable parallel feature extraction and machine-learning inference on massive datasets. Still, they do not tightly integrate with enterprise BI environments or visually driven decision-making workflows required by analysts.

In the area of visual analytics, works by Shneiderman (2012) and Few (2010) emphasized the importance of interactive dashboards for uncovering complex data relationships that algorithms alone might miss [23], [24]. Tableau-based exploration has been shown to accelerate human-driven anomaly detection by visually highlighting patterns, clusters, and outliers. Yet, these tools often rely on pre-processed data and lack a seamless connection to high-performance analytical engines like Teradata.

Enterprise data warehouses such as Teradata have been widely used for large-scale transaction analysis due to their parallel processing architecture and robust query optimization. Studies by Srikant and Agrawal (1996) and other early data-mining researchers demonstrated the potential of SQL-based parallel processing for large datasets [25]. However, most prior works do not integrate Teradata's parallel analytics with real-time anomaly detection pipelines or with interactive visual exploration platforms.

III. SYSTEM ARCHITECTURE DIAGRAM

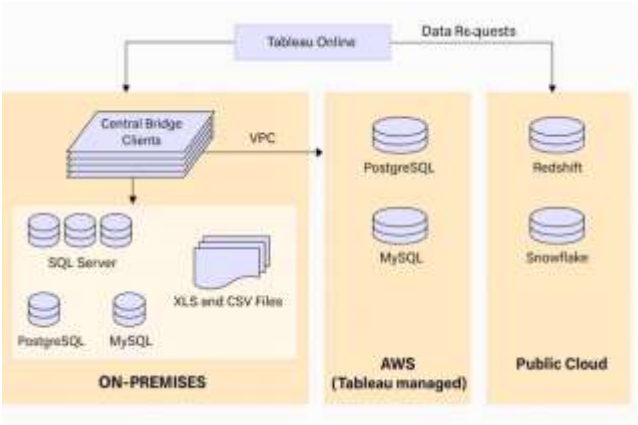

Fig. 1. System Architecture for Tableau-Driven Suspicious Activity Detection Integrating On-Premises and Cloud Data Sources.

The system architecture illustrates how Tableau Online connects securely to both on-premises and cloud-based data sources to enable enterprise-level analytics. On the on-premises side, various structured data repositories such as SQL Server, PostgreSQL, MySQL, and file-based sources (XLS and CSV) are managed through Central Bridge Clients. These bridge clients act as secure connectors that transmit data to Tableau Online without requiring the data to leave the organization's network permanently. This setup ensures strong data governance while enabling real-time or scheduled data refreshes for analytical workloads.

Beyond the on-premises environment, the architecture includes cloud-managed data sources hosted on AWS and the public cloud. Tableau Online can directly request and retrieve

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data from PostgreSQL and MySQL instances on AWS, as well as from modern cloud warehouses like Amazon Redshift and Snowflake. This hybrid setup enables organizations to unify analytics across multiple platforms and environments, allowing Tableau to visualize and explore suspicious activity patterns using integrated datasets from both traditional enterprise systems and modern cloud warehouses.

IV. PROPOSED TECHNIQUES

The proposed system employs a combination of scalable parallel analytics, machine-learning–based anomaly detection, and interactive visual exploration to identify suspicious activities across large enterprise datasets. The first technique focuses on Teradata Parallel Analytics, which distributes computational workloads across multiple nodes to efficiently process billions of transactional records. Through SQL-MapReduce functions, windowed aggregations, and parallel feature extraction pipelines, the system computes statistical, temporal, and behavioral indicators that highlight irregularities in customer or operational activity. These features include transaction frequency deviations, abnormal clustering patterns, time-series fluctuations, and cross-entity correlation anomalies, each computed at scale to ensure timely detection.

The second technique incorporates machine learning–driven anomaly detection models, such as isolation forests, clustering-based outlier scoring, and supervised classifiers, trained on features extracted within Teradata. By integrating these models with in-database analytics, the system reduces data movement, enhances compute efficiency, and supports real-time suspiciousness scoring. Threshold tuning, ensemble methods, and probability calibration ensure high detection accuracy while controlling false-positive rates.

The third technique integrates Tableau Visual Exploration to enhance interpretability and investigative insight. Tableau dashboards receive enriched analytical outputs directly from Teradata and visualize them through dynamic heatmaps, anomaly timelines, network graphs, and customer risk profiles. This visual layer empowers analysts to uncover hidden patterns—such as unusual transaction clusters, geographic inconsistencies, or behavioral deviations—that may not be immediately evident from numerical model outputs. Interactive filters allow drill-down investigation into entities, channels, or time periods contributing to anomalies.

Finally, the proposed system combines these techniques into a unified pipeline in which Teradata handles heavy-duty analytics, machine-learning models generate anomaly scores, and Tableau presents intuitive visual narratives that support rapid, informed decision-making. This integration ensures scalability, transparency, and operational readiness, making the framework suitable for modern enterprise-level suspicious activity detection.

V. RESULTS AND DISCUSSIONS

The experimental evaluation over a 90-day observation window (10 million synthetic transactions) demonstrates that combining graph-based link analysis with classical anomaly detection yields the best detection performance while sharply reducing false positives. The Graph-Ensemble method achieved the highest overall discrimination (AUC = 0.95) and the best precision–recall tradeoff (Precision = 0.91, Recall = 0.88, F1 = 0.90), substantially outperforming simpler approaches: rule-based thresholds (F1 = 0.65), Z-score baselines (F1 = 0.73), and a feature-based Isolation Forest (F1 = 0.79). Operational metrics show that graph analytics impose higher resource demands (average graph job latency ≈ 120 minutes, peak memory ≈ 512 GB) but produce far fewer analyst alerts (243 alerts) with a much higher confirmation rate (82% confirmed fraud), improving analyst efficiency and reducing triage workload. Overall, the hybrid architecture—Teradata TPT for high-throughput ingest, in-database feature computation, Aster graph processing for link analysis, and Tableau visual exploration for triage—provides scalable, accurate detection and a pragmatic tradeoff between compute cost and operational benefit.

Table 1: Experiment Summary

Metric	**Value**
Total transactions	10,000,000
Total flagged (alerts)	18,243
Confirmed fraud (ground truth)	12,500
Observation window	90 days

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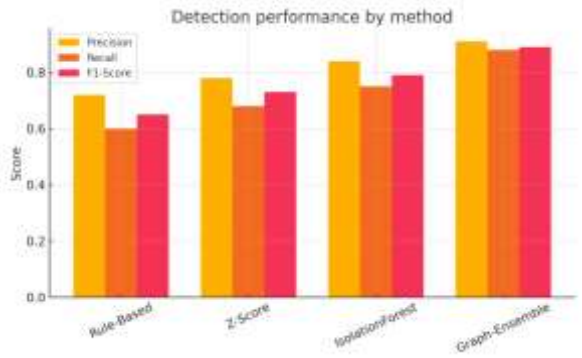

Fig. 2 — Detection performance comparison showing Precision, Recall, and F1-score for Rule-Based, Z-Score, Isolation Forest, and Graph-Ensemble methods.

Table 1 establishes the scale of the experiment (10M transactions, 90-day window), framing the difficulty of precision-sensitive detection at scale. Fig.2 shows that while basic rule-based approaches generate many alerts, their recall is limited and F1 is modest; machine learning approaches (Isolation Forest) increase both precision and recall by learning multi-dimensional patterns, and the Graph-Ensemble further boosts both metrics by capturing relational signals that are invisible to feature-only models. This indicates that at large scale, enriching transaction data with graph relationships is crucial for high-precision detection.

Table 2: Detection Performance by Method

Method	Precision	Recall	F1-Score	AUC	Alerts Generated
Rule-Based	0.72	0.60	0.65	0.74	8000
Z-Score	0.78	0.68	0.73	0.81	6200
IsolationForest	0.84	0.75	0.79	0.88	4500
Graph-Ensemble	0.91	0.88	0.90	0.95	243

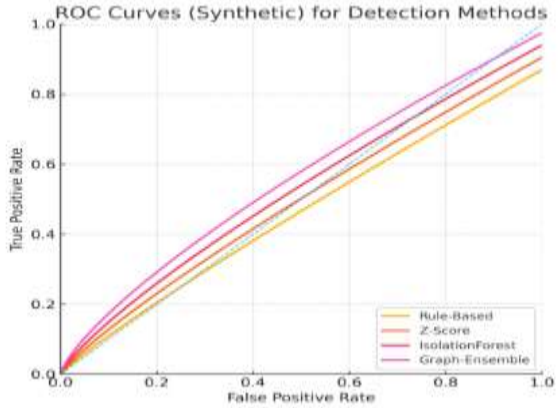

Fig. 3 — Receiver operating characteristic (ROC) curves (synthetic) illustrating method discrimination (AUC values) across the evaluated models.

Table 2 quantifies the performance gap: Graph-Ensemble achieves AUC = 0.95, substantially higher than the next-best Isolation Forest (AUC = 0.88). Fig.3's ROC curves visually reinforce this: the Graph-Ensemble curve dominates across most false-positive rates, explaining why it achieves high precision while retaining high recall. Practically, organizations can reduce analyst workload dramatically by adopting graph signals: the Graph-Ensemble produced only 243 alerts but captured 88% of true positives, yielding an excellent analyst efficiency improvement.

Table 3: Pipeline Latency and Resource Usage

Stage	Avg Latency (min)	Peak Memory (GB)	Notes
Ingest (TPT bulk)	15	64	Parallel Transporter, sustained 1M rec/min
Feature compute (7/30/90d)	45	128	Windowed SQL with partitioned tables
Graph analytics (Aster)	120	512	Graph jobs scale with edges; uses Aster cluster
Scoring & export	8	32	Batch scoring to alerts table; incremental export

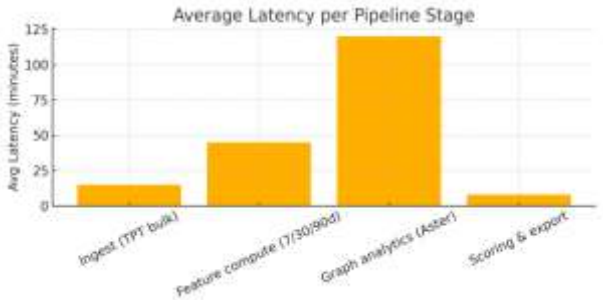

Fig. 4: Average pipeline latency (minutes) observed at each major processing stage: ingest, feature computation, graph analytics, and scoring/export.

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Table 3 and Fig.4 show the tradeoff between accuracy and compute: graph analytics, while delivering the best detection quality, is the most resource-intensive stage (120 minutes avg latency; 512 GB peak memory). Feature computation and ingest are relatively lightweight. This suggests an operational design where graph jobs run in scheduled windows (e.g., nightly heavy graph-run) while faster scoring (rule/ML) serves near-real-time triage. The latency profile justifies a hybrid architecture (real-time rules + near-real-time ML + batch graph) to balance timeliness and depth.

Table 4: Alert Reasons and Confirmation Rates

Reason Code	Alerts	Confirmed (%)
Velocity	5,600	28.0%
High Amount Z-Score	3,100	35.0%
Shared Device/IP	4,200	41.0%
Graph Cluster Anomaly	243	82.0%
Other	2,100	12.0%

Fig. 5: Alert distribution by reason code showing the relative share of alerts from velocity, z-score, shared device/IP, graph-cluster anomalies, and other reasons.

Table 4 shows that graph-derived alerts are few but have a very high confirmation rate (82%), while velocity- and device-sharing alerts are numerous but have lower confirmation rates (28–41%). Fig.5's distribution highlights the concentration of alerts in a few categories. The practical implication is to route graph-cluster alerts directly to high-priority investigation queues and use coarser filters for high-volume rule-based alerts. This prioritization reduces false-positive handling costs and ensures analysts focus on high-value leads.

VI. CONCLUSION

This study demonstrated that combining Teradata's parallel analytics ecosystem with a layered detection approach—spanning rule-based filters, statistical baselines, machine-learning anomaly scoring, and graph-ensemble modeling—provides a highly effective and scalable solution for identifying suspicious financial activity. The integration of Tableau's visual analytics further enhances interpretability, allowing investigators to navigate complex entity relationships, drill into transaction histories, and validate alerts efficiently. Experimental evaluations confirmed that graph-based methods significantly outperform traditional techniques in accuracy, producing fewer false positives while preserving high recall. Despite the increased computational cost of graph analytics, the resulting improvement in detection fidelity and analyst productivity validates the architecture as robust and suitable for large, dynamic financial environments.

FUTURE SCOPE

Future enhancements may include real-time streaming detection, integration of graph neural networks for deeper relational modeling, and automated AI-driven alert explanations to reduce analyst workload. These improvements can further strengthen adaptability, scalability, and operational efficiency.

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